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THREE-TIER NEURAL NETWORK FORECAST OF POWER OUTPUT FROM A MINI PHOTOVOLTAIC PLANT IN OGUN STATE, NIGERIA

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Abstract
The unreliability of solar energy as an alternative source of electricity is a source of concern to stakeholders. To mitigate this challenge, researchers have proposed photovoltaic (PV) power output forecasting which is aimed at predicting the power output of a PV plant. This study develops and validates a three-tier neural network model for forecasting the output of a mini PV plant located in Ifo, Ogun State, Nigeria. The result of the developed model was compared with a state-of-the-art mathematical model using three statistical tools of mean bias error (MBE), root mean square error (RMSE) and mean average percentage error (MAPE) over a period of three months. From the monthly evaluation, results reveal that the MBE values of the three-tier model were lower than that of the mathematical model with a difference of 0.08, 0.03, and 0.09. In terms of the RMSE, the difference between the three-tier and mathematical model values are 0.07, 0.01 and 0.02. The MAPE differences between the two models were 0.05, 0.00 and 0.02. In all the obtained results, the three-tier model showed a consistently better performance than the mathematical model which validates it as a reliable tool for forecasting the power output of a PV plant.

Keywords – PV cell power output, Mathematical modelling, Artificial neural network, PV power forecasting

1. Introduction

Inadequate supply of electricity in Nigeria is a problem that has defied many solutions for decades despite several theoretical and practical attempts made by successive governments to solve the challenge. However, it is believed that a systematic investment in renewable energy would solve this problem of inadequate supply of electricity faced by Nigeria. Also, it was predicted that future power systems would have an increased share of variable renewable energy (wind and solar PV) (Ueckerdt *et al.,* 2015).

Nigeria is known for her abundant possession of one of such sources, solar. Thus, the country is expected to tap into this resource to tackle her electricity challenge. However, despite the excess availability of solar radiation in Nigeria, the country has not benefited much from the use of photovoltaic system as a means of generating electricity. Apart from high cost, two reasons for this include variability and uncertainty, that is, photovoltaic power output exhibits variability at all timescales and that variability is not easy to predict (Pelland *et al.*, 2013). To reduce the impact of the two factors on solar systems, experts have suggested the use of forecasting methods to predict the power output of solar systems (Tuohy *et al.,* 2015, Voyant *et al.*, 2017). Solar forecasts are used by power sector stakeholders like system operators to schedule generation and ensure adequate flexibility to manage changes in power output (Tuohy *et al.,* 2015).

Forecasting methods can be classified as physical or statistical. The physical approach uses solar and PV models to generate PV forecasts. On the other hand, the statistical approach uses historical data to "train" models, with little or no reliance on solar and PV models (Pelland *et al.*, 2013). Some of these methods include Time Series Prediction with Statistical Learning, Sky Imagers, Satellite Imaging, Numerical Weather Prediction and Ensemble Forecasting. Forecast can be carried on different time horizons which includes intra-hour, intra-day and day-ahead. This study uses a blend of both the physical and statistical approach to design, develop and

validate a three-tier neural network forecast of power output in a 6KVA PV plant situated in the Department of Computer and Electrical Engineering at the Olabisi Onabanjo University (OOU), Ifo, Ogun State, Nigeria.

A study by Kardakos *et al.* (2013), presented two practical methods for the forecast of electricity generation of grid-connected PV plant. The first method is based on seasonal ARIMA time-series analysis and was further improved by integrating short-term solar radiation forecasts derived from Numerical Weather Prediction (NWP) models. The second method used artificial neural networks with multiple inputs. Day-ahead and rolling intra-day forecast updates were implemented to evaluate the forecast errors. The two methods were then compared in terms of the Normalized Root Mean Square Error (NRMSE). Test results revealed that, the methods that made use of available external solar radiation data, namely, the modified SARIMA model and the ANN models were preferable, since they led to considerably improved day-ahead forecasts and lower NRMSEs as compared to the persistence model or the pure SARIMA model. In another study by Mellit *et al*. (2014), a 1-year database of solar irradiance, cell temperature and power output produced by a1-MWp photovoltaic plant in Southern Italy was used for developing three distinct artificial neural network (ANN) models. The models were applied to three typical types of day (sunny, partly cloudy and overcast). Results from the study showed that for ANN-based models that use forecasted data and the present or the past values of the power output (P) as input, the $\{P(t+1) = f(G_i(t+1), T_c(t+1), P(t))\}$ where P = power, t time (in seconds), , T_c = temperature, and G_i solar irradiance can produce good results compared to those using only forecasted weather data or the past values of the power output. The correlation coefficient in all ANN-models was greater than 98%, which means that the power output can be estimated with reasonable accuracy.

In a similar study by Alberto *et al*. (2015), an assessment of the day ahead forecasting activity of the power production by photovoltaic plants was carried out. The work presented a new hybrid method called Physical Hybrid Artificial Neural Network (PHANN) based on an Artificial Neural Network (ANN) and PV plant clear sky curves. The authors compared the accuracy of the presented method with a standard ANN method. Results revealed that the new PHANN method was more effective than traditional ones especially with sunny days, where the error reduction reaches 50%. All the error indicators increased during unstable days when the weather conditions suddenly changed with time. Also, a significant increase in WMAE% was observed in extremely cloudy days.

Leva *et al.* (2017) presented a PV energy forecasting method based on ANN. The error assessment, according to the error definitions shows that the ensemble error was smaller than those obtained by the single trials. It was revealed that the method accuracy was strictly related to the historical data pre-process step and to the accuracy of the historical data set used for the training step. The trends of the errors showed that the accuracy in the sunny days was higher, while in partially cloudy and cloudy days the overall efficiency is slightly different.

In another study by Dimopoulou *et al.* (2017), two different methods were applied to forecast the next hour PV power using artificial neural networks (ANN). In the first case, the weather parameters of solar irradiance and ambient temperature were predicted, the output was fed to the developed model of the PV installation and the next hour PV power was computed. In the second case, the PV power was directly predicted. The performance of the applied ANNs was then compared with the respective outcomes from the persistence models. In each case, the result showed that the applied ANN outperformed the persistence model. Also, during the evaluation phase the extracted annual energy results were compared with the respective registered data from

the installed meters. In both cases, the results approximated the reality, though in the first case, there was difficulty in identification and representation of malfunctions in the operation of the PV plants. The difficulty was due to snow accumulation on the panels which caused minor deviations.
From the literature reviewed, it can be observed that no study appears to have been carried out on the practicability of a forecast model for the Nigerian environment hence the need for this study. This study therefore, aims at developing a forecast model for predicting the power output of a PV plant located in Ifo, Ogun State, Nigeria.
The study is organized as follows, section 2.0 gives a brief overview of the three-tier neural network. Section 3.0 describes the methodology of data collection, training and analysis. In section 4.0, the results and discussion are presented while section 5.0 concludes the study.

2. Materials and Methods

2.2 Three-Tier Neural Network

This study used a three-tier neural network approach shown in Figure 1 to forecast the power output of a mini PV plant one hour ahead from the solar global irradiance and the ambient temperature current values. The neural network toolbox in MATLAB R2013b was used. Three-tier neural network method comprises of a first two-tier module used to forecast the solar irradiance and ambient temperature values that served as input to the third tier. The first two-tier were developed from the year 2016 solar radiation and temperature data obtained from the Nigeria Meterological Agency (NIMET), Ibadan office while the third-tier was developed using the data obtained from the ET6415 BND Solar Charge Controller installed in the site where this study was carried out. The power output of the third-tier provides the output power of the mini PV plant. The output of the first two-tiers (radiation forecast and the temperature forecast) is also fed into the Perpiñan model with the aim of comparing its predicted power output with the output of the ANN model.

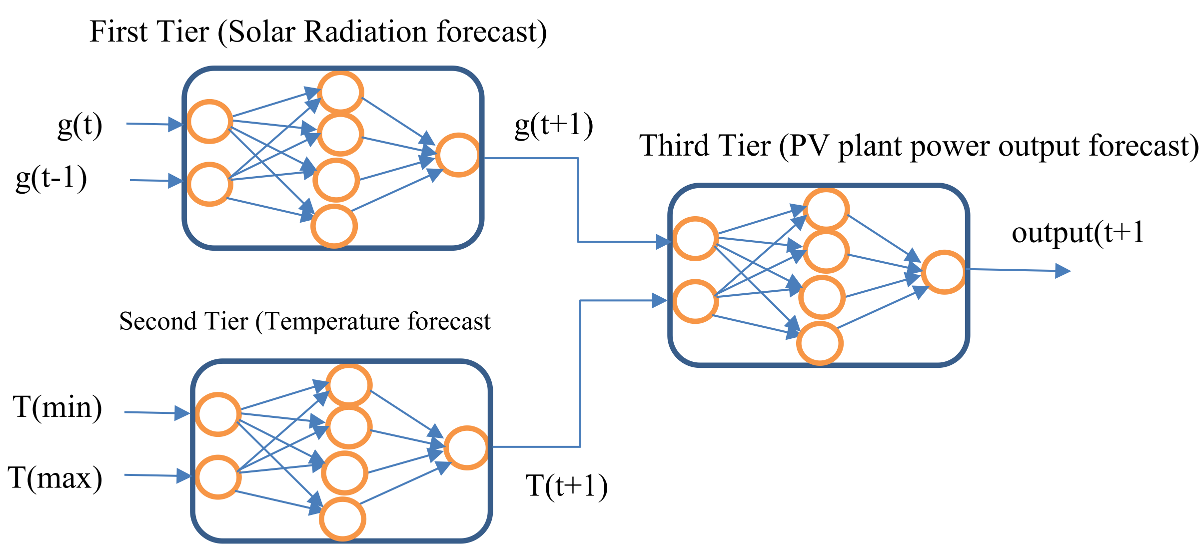

Figure 1: Three-Tier Neural Network

The first tier uses the current and previous hours solar radiation value to predict solar global irradiance in the next hour. The input to this layer is the current global radiation value g(t) and the value of the previous hour g(t-1). The training of the neural network was done using the 2016

solar radiation data as obtained from the Nigeria Meteorological Agency (NIMET). For the second tier, the input is the minimum T(min) and maximum T(max) temperature values of the hour while the training was done using the 2016 temperature data also obtained from NIMET. The outputs of the first and second tier serves as input to the third tier.

2.3 Methodology

In this study, a three-tier neural network forecast method using a 6KVA mini PV plant was developed and validated situated in the Department of Computer and Electrical Engineering at located in Ifo, Ogun State, Nigeria as a case study. The plant has been operational for two years and it serves as an alternative energy source for the Computer and Electrical Engineering building. First the ambient temperature and the solar irradiance of the site where the PV plant is installed were obtained for year 2016 from NIMET since the PV energy production is highly dependent on these two parameters. The daily output of the PV plant shown in Figure 2 – 4 for the same year was also monitored at an hour interval using the ET6415 BND solar charge controller manufactured by EPSOLAR Technologies and shown in Figure 5. The obtained data from NIMET and the daily output of the PV plant is then used to develop and train an artificial neural network model. MATLAB was used to simulate a mathematical analytical model (Perpiñan *et al.*, 2006) that represents the relationship between solar irradiance, ambient temperature and power output of a PV panel. The described mathematical model is shown in Equation 1. To evaluate the performance of the developed ANN model, the temperature and solar radiation forecast values were used as input to both the mathematical and ANN models. A direct PV power output measurement was also carried out from the array of solar cells shown in Figure 2 – 4 which was used as the benchmark for the correct PV power output values. The three results (ANN model, mathematical model and direct measurement) were compared, and the conclusion was drawn based on our observations. According to Perpiñan model, the DC output power of one module is related to the following parameters as described below:

$$P_{DC} = \eta\text{ext losses}.(\mathbf{P}\text{peak}\cdot\left(\frac{(\mathbf{Geff})}{\mathbf{G}^{\times}}\right)\cdot[\mathbf{1}-\boldsymbol{\beta}(T_c - \mathbf{T}^{\times}c)]) \quad (1)$$

where: ηext losses are losses for modules mismatching, diodes and dirt (9%);
$\mathbf{P_{peak}}$ is the rated power of one module (W);
$\mathbf{G_{eff}}$ is the effective global radiation (W/m²);
G*is the radiation in standard conditions (1000W/m²);
$\boldsymbol{\beta}$ is the temperature losses coefficient (0.005/°C);
Tc is the operation cell temperature;
$\mathbf{T}^{\times}$c is the standard operation cell temperature (25°C).

The operation temperature **T**c was calculated using Equation (2), as follows:

$$\mathbf{T_C} = \mathbf{T}\text{amb}+(\text{NOCT} - \text{TNOCT,std})\cdot\left(\frac{(\text{Geff})}{\text{GNOCT}}\right) \quad (2)$$

where: **T**amb is the ambient temperature (°C);
NOCT is the nominal operation cell temperature (47°C);
TNOCT,std is the ambient temperature at NOCT conditions (20°C);
GNOCT is the radiation at NOCT conditions (800W/m²).

Figure 2: PV panel Array A

Figure 3: PV panel Array B

Figure 4: PV panel Array C

Figure 5: ET6415 BND Charge Controller

2.4 Data Training

The three set of data (solar irradiance, ambient temperature, PV power output) were divided into three categories that includes training data (70%), validation data (15%) and testing data (15%) as recommended in ANN. For the three neural networks, the number of neurons used in the hidden layer is ten. The algorithm used to train the three network is the Levenberg–Markquard algorithm. This algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions (Lourakis *et al., 2005).* The algorithm is suitable for training small and medium-sized problems in the artificial neural-networks field, thus, it was selected for use in this work. The update rule of Levenberg–Marquardt algorithm is presented in Equation 3 as

$$W_{k+1} = W_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \tag{3}$$

where: μ is the combination coefficient with a positive value.
I is the identity matrix
e is the training error
W is the weight vector
J is the Jacobian matrix

2.5 Data Analysis

There are several statistical tools for evaluating the performance of mathematical models. However, for this work, we selected three tools that includes Mean Bias Error (MBE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The Mean Bias Error (MBE) provides information on the long-term performance of the correlations by allowing

a comparison of the actual deviation between simulated and measured values term by term. The ideal value of the MBE is zero. The MBE is given in equation 4 as

$$\mathrm{MBE} = \sum_{k}^{n} = 1 \left(\frac{y_k - x_k}{n}\right) \quad (4)$$

where:
y_k = kth simulated value,
x_k= kth measured value and
n = total number of days.

The root-mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values observed from the thing being modelled or estimated. RMSE is a good measure of precision and provides information on the short-term performance of a model. The value of RMSE is always positive, representing zero in the ideal case. A low RMSE is however desirable.
The RMSE may be computed from equation 5 as:

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(\frac{y_k - x_k}{x_k}\right)^2 k} \quad (5)$$

The Mean Absolute Percentage Error (MAPE) value provides the percentage deviation between the calculated and measured data. The ideal value of MPE is zero.

The Mean Absolute Percentage Error is given in equation 6 as:

$$\mathrm{MAPE} = \frac{100}{n}\sum_{k=1}^{n}\frac{(y_k - x_k)}{x_k} \quad (6)$$

3. Results and Discussion

Figure 6-8 shows the correlation between outputs and targets data for the three-tier model

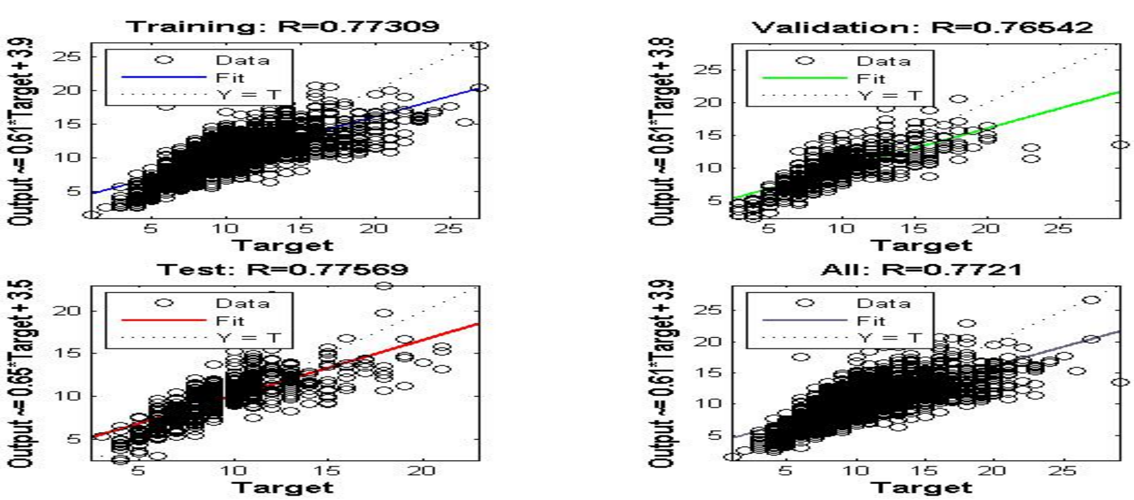

Figure 6: Correlation between outputs and targets irradiance data (Tier 1)

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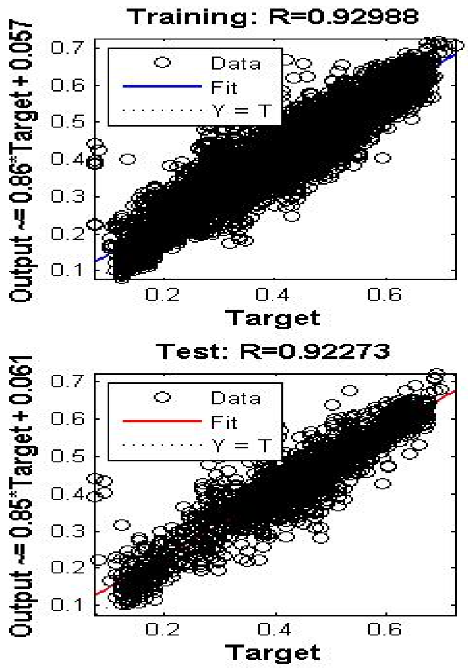

Figure 7: Correlation between outputs and targets temperature data (Tier 2)

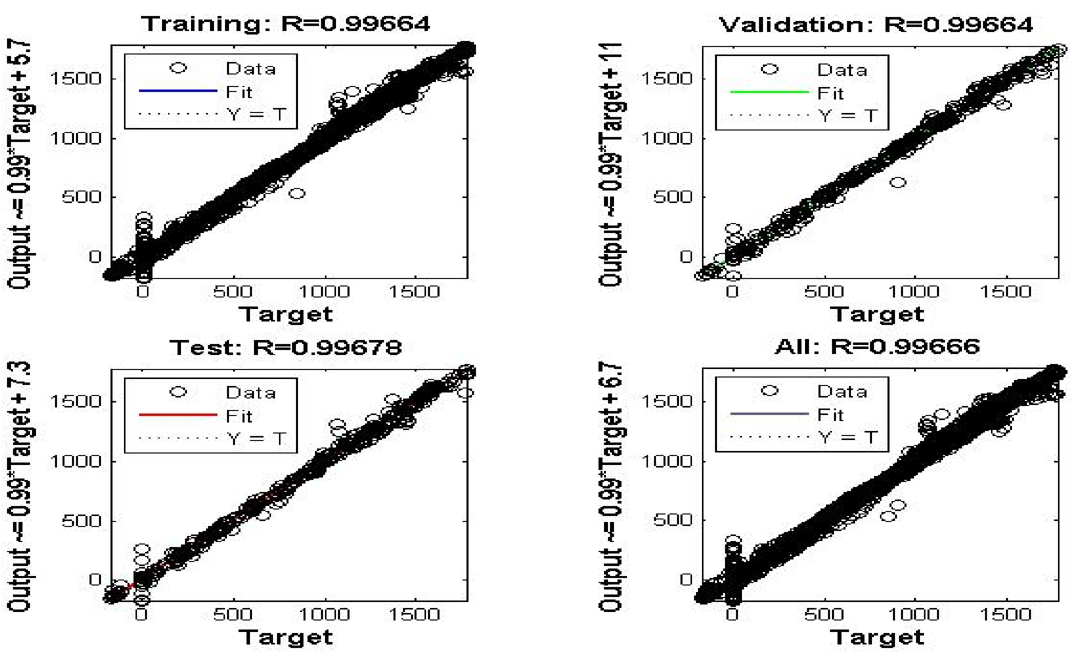

Figure 8: Correlation between outputs and targets power output data (Tier 3)

The average hourly power output from the three-tier model, mathematical model and measured power from the mini PV plant for a three-month period (January to March) were collected and are shown in Figure 9 – 11.

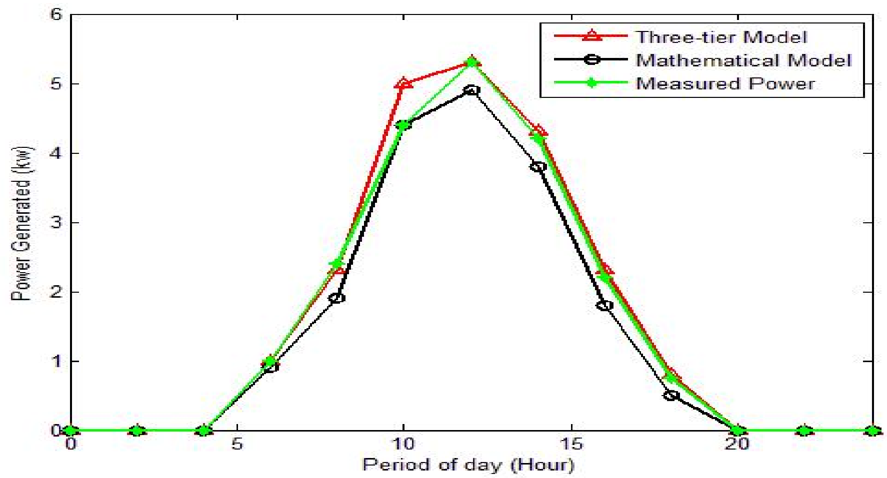

Figure 9: Average Hourly Power Output for January 2017

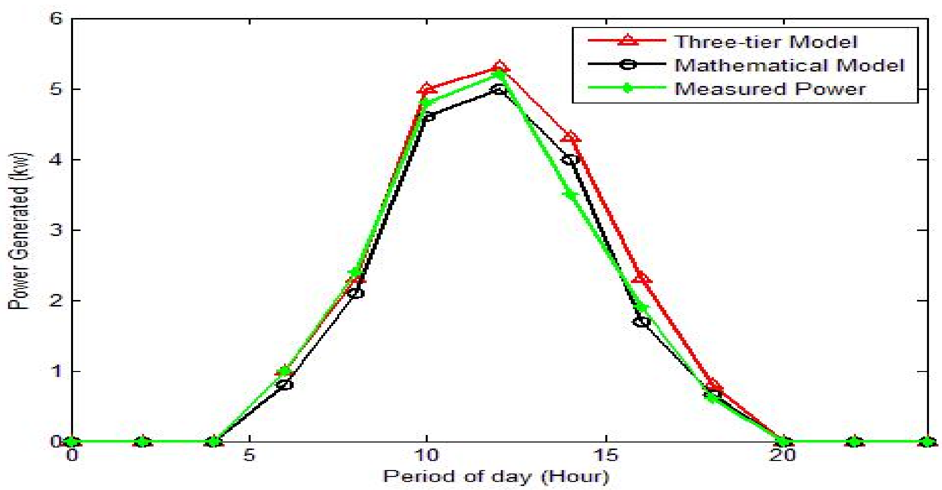

Figure 10: Average Hourly Power Output for February 2017

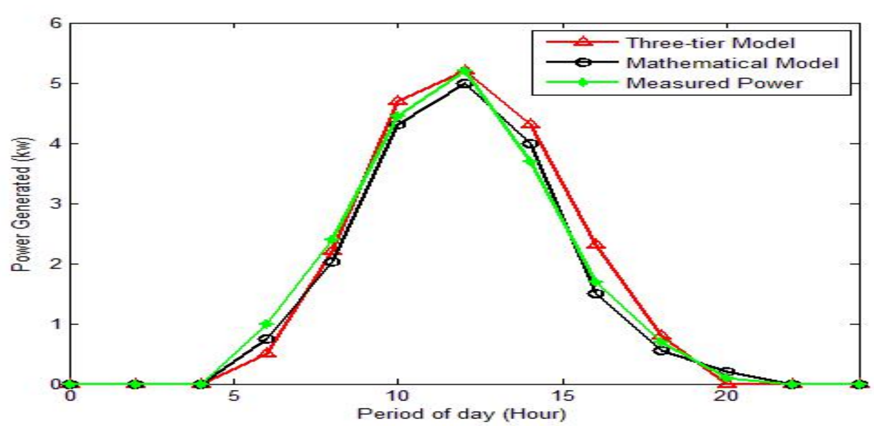

Figure 11: Average Hourly Power Output for March 2017

The MBE, RMSE and MAPE values for the generated power values shown in Figures 9, 10 and 11 were evaluated using equation 4, 5 and 6. The results are shown in Table 1

Table 1: Summary of Results from the Statistical Tools used to Evaluate the Models

Month	MBE		RMSE		MAPE	
	Three-tier	Math.	Three-tier	Math.	Three-tier	Math.
January	0.15	0.23	0.28	0.35	0.24	0.29
February	0.18	0.21	0.30	0.31	0.27	0.27
March	0.16	0.25	0.27	0.29	0.26	0.28

From the result shown in Table 1, the MBE values of the three-tier model were lower than the mathematical model with a difference of 0.08, 0.03, and 0.09 which signifies a better performance. In terms of the RMSE, the difference between the three-tier and mathematical model values are 0.07, 0.01 and 0,02. The MAPE differences between the two models are 0.05, 0.00 and 0.02. In all the obtained results, the three-tier model showed a consistent better performance than the mathematical model.

4. Conclusion

This study addressed the challenge of unreliability in PV systems by proposing a three-tier neural network forecast model for predicting power output in a PV plant situated in Nigeria. The neural network was trained using ambient temperature and the solar irradiance data of the plant location. The daily output of the PV plant was then monitored and compared with predicted output of the developed network and a mathematical model using three statistical tools of MBE, RMSE and MAPE. Results obtained revealed that the three-tier model performed better than the mathematical model making it a more reliable tool for predicting the power output from a PV plant. In future, the authors intend to improve the performance of the three-tier network by adding year 2017 radiation and temperature data to the training dataset.

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